Effects of Visual Fidelity on Task Performance and Mental Workload in IVEs

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Abstract –

Visual fidelity affects the user experience and performance in virtual environments. While past studies have explored its effects, most have relied on qualitative measures, and few quantitative studies have specified visual quality standards. This study examined the influence of visual fidelity on task performance and mental workload in immersive virtual environments (IVEs). Two environmental models were tested in virtual reality (VR) and mixed reality (MR): a high-visual quality model featuring detailed materials, realistic lighting, and outdoor scenery, and a low-fidelity research model with basic colors, dimensional lighting, and no external views. Sixty participants completed cognitive tasks (digit span, spatial working memory updating, go/no-go), while the EEG measured mental workload. The results showed that high-fidelity increased the cognitive load in complex tasks, whereas MR environments supported better performance. These findings emphasize the need to balance realism and cognitive demands to optimize virtual experiences.

Keywords –

Immersive Virtual Environments; Visual Fidelity; Task Performance; Mental Workload

1 Introduction

Immersive Virtual Environments (IVEs) are increasingly being used in research and industry for training, simulation, and entertainment. Advancements in head-mounted display (HMD) hardware and software have enhanced visual fidelity by incorporating detailed textures, realistic lighting, and function-focused representations [1]. Visual fidelity, defined as the level of realism and detail in rendered virtual environments (VEs), is widely assumed to enhance the user's sense of presence (SoP), the subjective perception of "being there" [2].

However, previous studies have primarily focused on qualitative methods, such as surveys and interviews [3], leaving the impact of visual fidelity on objective measures of task performance and mental workload less explored. Task performance is a critical factor in indoor behavior and influences business and educational outcomes [4,5]. Mental workload, which represents cognitive effort during work or study, is influenced by complexity and environmental outcomes [6,7]. While high-fidelity elements enhance realism and immersion, they may also increase the cognitive load by demanding greater processing resources, particularly in scenarios requiring complex decision-making or problem-solving within Virtual (VR) and Mixed Reality (MR) [8,9].

This study aimed to investigate the influence of high and low visual fidelity on task performance and mental workload in IVEs. By comparing VR and MR settings, we provide insights into leveraging visual presentation to balance performance and cognitive demands.

2 Literature Reviews

Visual fidelity is often correlated with user engagement, presence, and satisfaction with a VEs [10]. Previous studies have suggested that realistic lighting and detailed textures significantly enhance SoP [11,12]. However, high-fidelity elements also require greater computational resource and may inadvertently increase the cognitive load [13]. Experimental investigations on IVEs have shown that variations in environmental realism can significantly affect user experience [14,15]. Beyond a certain threshold, further enhancements in graphical detail may yield diminishing returns on engagement and fail to substantially improve task performance [16].

Milgram and Kishino [17] described the Reality-Virtuality Continuum, bridging the gap between fully virtual and real environments. Whereas VR places the user in a completely simulated space, whereas MR overlays digital objects in the real-world. This dual processing may lead to different cognitive demands than those in the VE. Supporting this notion, Hong et al. [18] demonstrated that users' subjective evaluations of an urban soundscape did not significantly differ between real and IVEs, suggesting a certain level of equivalence in the perceived experience.

Physical environmental factors, such as ceiling height, nature elements, and window size, are well known to influence work performance [19–22]. The translation of these insights into IVEs, particularly those designed with varying degrees of visual fidelity, is an area of ongoing research. High visual fidelity can enhance the user's SoP and realism in virtual experiences. However, they may also increase the cognitive load, especially during complex decision-making or problem-solving tasks. For instance, a study on visuospatial problem-solving in MR environments found that although high-fidelity visuals improved task accuracy, they also led to longer completion times, indicating increased cognitive effort [23]. Similarly, research on the cognitive load in 3D Ves suggests that higher visual complexity can elevate the cognitive load, potentially affecting user performance [9].

This gap in understanding, explains how visual fidelity in immersive environments influences task performance, mental workload. By systematically examining user performance and mental workload across varying levels of visual realism, we aimed to clarify whether increased visual fidelity truly benefits VE users. While previous research has highlighted the potential of high-fidelity environments to enhance SoP and immersion, their impact on practical outcomes, such as cognitive efficiency and task performance, remains underexplored.

3 Methods

3.1 Experimental Settings

3.1.1 Physical Space

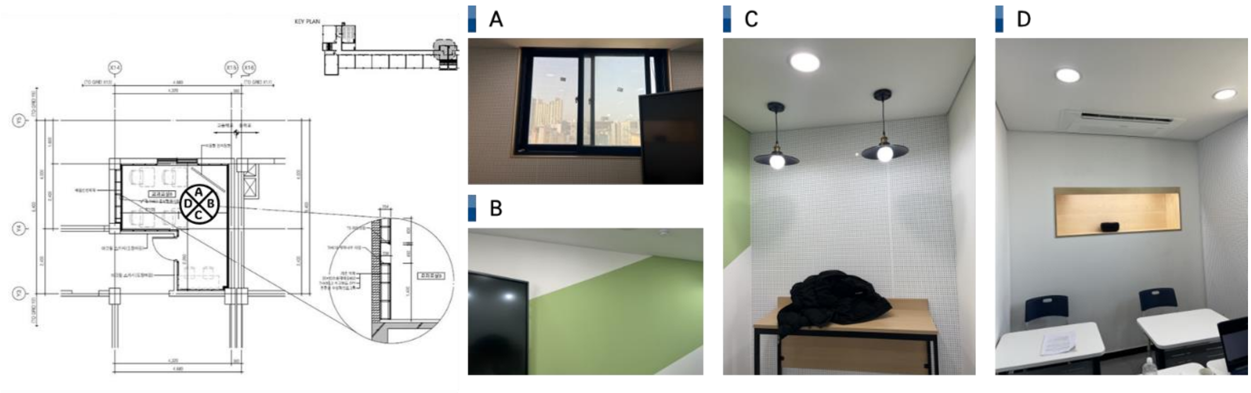
An L-shaped classroom was selected as the experimental setting for this study, because its layout is particularly relevant for examining the cognitive load and occupant engagement while reducing distractions [24]. The physical space used was 15.5 m^2 L-shaped educational facility in Seoul, Republic of Korea. Thes room was furnished with basic furniture, including four tables and chairs, a television, two pendent lights, bar tables and chairs, and air conditioners. In addition, the wall interior was painted using a green diagonal design and punched plate finishing. The features of this room, along with general images, are shown in Figure 1.

3.1.2 Virtual Spaces

Two distinct VEs were created in this study. First, the virtual setting was modelled in Unity 3D using a 3D model developed from the original CAD floor plan in Revit software. Second, the 3D modelling file was exported as an fbx file and imported into the Unity 3D environment. Finally, detailed virtual settings were designed in the Unity 3D engine such as texture, lighting, and outdoor scenery. This design process was performed based on different visual fidelity levels, with high and low quality implemented in each VR and MR devices.

3.1.3 Visual Quality Levels in VEs

Each virtual environment was presented at two visual quality levels, following the framework outlined by Graham et al. [25]. The authors classified visual fidelity into two levels of detail (LOD 1 and LOD 2) in VR environments, using identical base modelling files. In LOD 1, textures were applied to 3D models using a generic texture library available on software platforms



Floor Plan

Section Images

Figure 1. Floor plan and cross-section photos of the physical space

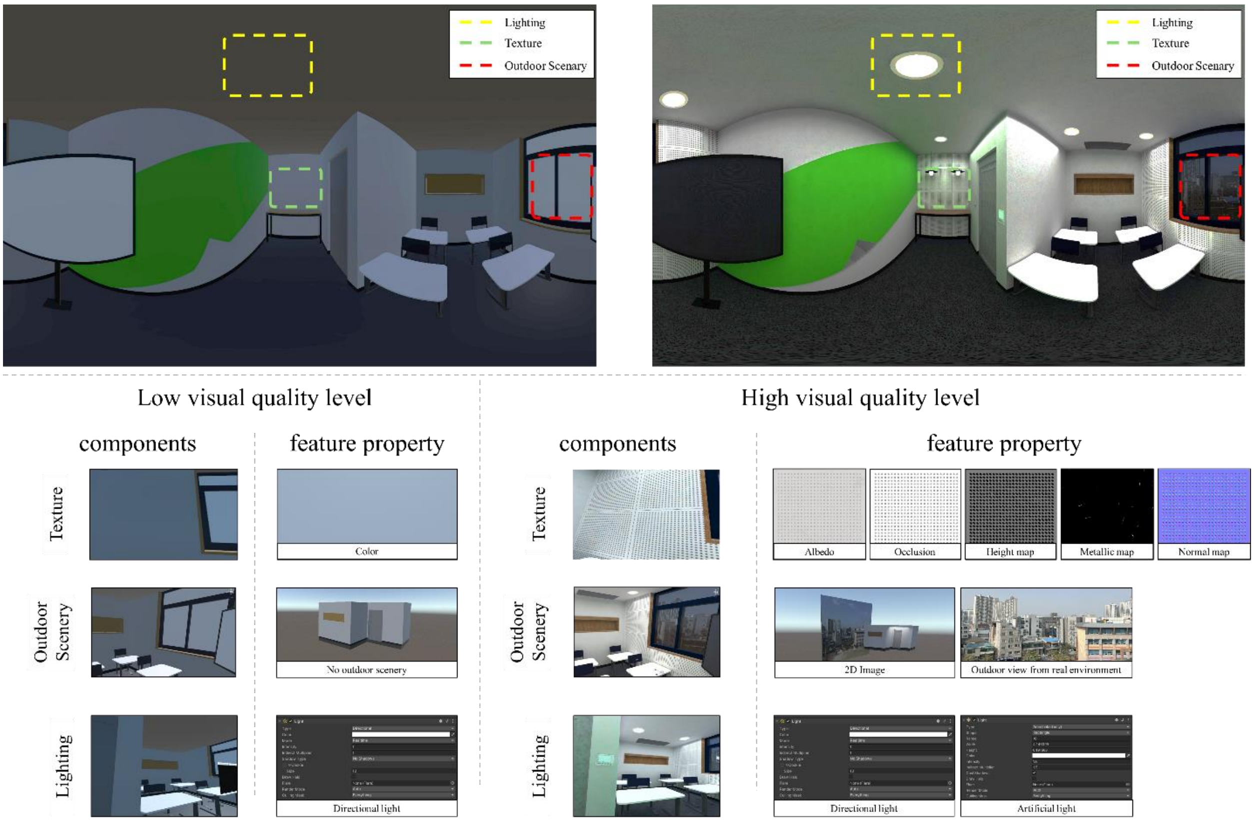


Figure 2. Description of LQ and HQ visual fidelity features in VEs

such as Autodesk Revit, Rhinoceros, or Unity 3D. Conversely, LOD 2 incorporates highly detailed texture features, leveraging advanced techniques such as detail maps (including normal, height, and adobe maps) or data derived from laser scanning and photogrammetry.

In this study, the High-Quality (HQ) visual fidelity level includes realistic artificial indoor lighting that enhanced the immersive quality of the environment. In addition, the outdoor scenery visible through windows was modelled using real photographs, further contributing to the realism of the virtual environment. However, the Low-Quality (LQ) visual fidelity level relies solely on directional lighting provided by Unity 3D, which simplifies the lighting setup. Unlike the HQ, the LQ does not include outdoor scenery, which results in a less immersive virtual experience.

3.2 Subjects

A one-way analysis of variance (ANOVA) was conducted. Based on the central limit theorem and assumption of normality in the distribution for statistical analysis, a sample size of 30 participants was used [26]. The specific sample size was calculated using G*power 3.1 software. We used an ANOVA: fixed effects, omnibus, one-way function with an effect size of 0.60 as the middle scale, an alpha error probability of 0.05, and a power level of 0.80 with three groups.

As the experimental groups were conducted using VR, MR, and real-world settings, a total of 50 participants was calculated, and 60 subjects were recruited, considering a dropout rate of 20%. All the study procedures were approved by the Institutional Review Board and Ethics Committee of Hanyang University (HYUIRB-202406-014). In total, 60 subjects participated in this study, none of whom had a history of mental or physical health problems. Among the 60 collected data points, three were excluded because of poor data quality, two from the HQ group and one from the LQ group.

The study sample consisted of 60 participants aged 20 – 32 years, reflecting the target demographics of university students. Among the participants, 42 were male, and 18 were female. The average age for male participants is 25.43 years, and the average age for female participants is 24.06 years. The overall average age of the sample is 25.02 years. The decision to recruit participants primarily in their twenties aligns with the study's focus on classroom environments, as university students represent the primary users

3.3 Measurements

3.3.1 Task Performance

Cognitive tests are widely used to assess domains such as executive function, attention, memory, intelligence, language ability, and reasoning [27]. These cognitive domains are regarded as key indicators of concentration and predictors of future job performance [28]. While specific cognitive requirements may vary depending on job demands, executive function, attention, and memory are fundamental to general work performance [29].

To evaluate productivity across different spatial environments, three cognitive tests were conducted, the 2-back test, spatial working memory updating, and go/no-go test. In an MR environment, where holographic information is overlaid onto the real world, the use of a traditional keyboard can be challenging for users. To address this limitation, cognitive tests that rely on simple button interactions, such as pressing a space bar or number keypads, were adopted.

The 2-back test presents sequential visual stimuli to the users, requiring them to memorize and respond correct time [30]. In the 2-back test, participants must identify when the current stimulus matches the one presented two steps earlier, necessitating continuous updating of information.

Spatial working memory updating was utilized to assess memory ability. The original test uses a 2x2 matrix displayed on the screen, in which a color-filled square briefly appeared in one spot before disappearing [31]. In the updated version of the test, a 3x3 blank square matrix was used to further assess participants' memory abilities.

The go/no-go test is an intuitive measure of participants' attention ability [32]. In this test, a green or checkerboard pattern sphere appeared on the screen to evaluate the response time and accuracy. This test effectively gauges participants' ability to focus, process stimuli, and exercise inhibitory control.

To quantify learning performance, accuracy and response time were recorded for all cognitive tests. The learning performance was calculated using Equation (1) and employed as the primary indicator [3].

3.3.2 Mental Workload

The experiments imposed a cognitive load on participants, making it necessary to quantify and measure this load. The cognitive load experienced by participants during the task increased as they completed the given assignments, with workload and stress being the primary factors involved in the process. To assess this, we used the EPOC X+ device to collect raw EEG data. Brainwave data were extracted from the frontal (AF3, F7, F3, FC5, FC6, F4, F8, and AF4), parietal (T7, P7, P8, and T8), and occipital lobes (O1 and O2 through 14 electrodes, capturing frequencies within the range of 0.16 to 43 Hz.

Raw data often contain noise, such as eye blinks, head movements, and muscle activity, which necessitates a noise removal process. A finite-impulse response (FIR) filter was applied to eliminate these artifacts, and data outside the 4-40 Hz range were discarded. Next, an independent component analysis (ICA) was performed to remove impractical features from the filtered EEG data. Finally, the collected EEG data were classified into theta, alpha, beta, and gamma wave categories using fast Fourier transform (FFT). This method, which is widely validated in neuroscience, allows for the differentiation of brainwave activity. In simple term, theta waves are typically active during states of relaxation [34], alpha waves during calmness [35], beta waves during thinking or when experiencing tension [36], and gamma waves during heightened focus and concentration [37].

To conduct an in-depth analysis of the cognitive load during tasks, the mental workload was calculated and used as indicators. The methods for measuring each indicator follow Equations (2) [38].

3.4 Research Procedure

Each experiment was conducted in the same classroom with a modelled environment to prevent misunderstandings regarding the spatial layout. Participants underwent a preparation phase that consisted of an explanation of
the experiment, a Short Portable Mental Status Questionnaires (SPMSQ), and a short training of VR and MR to familiarize themselves with the navigation and interaction features in VE. The SPMSQ was used to check whether the participants had cognitive impairment [39]. Including the preparation phase, all VE experiences using the HMD device were limited to two minutes to prevent motion sickness, cyber-sickness, and dizziness. To measure brainwaves, the participants wore an EEG device on the MR HMD. After the preparation phase, the subjects performed three cognitive tests in each experimental environment, and the accuracy rate, response time, and brain wave data were collected. Cognitive tests were conducted in random order to prevent ordering effects [28].

$$Learning\ Performance = \left[(Accuracy, \%)^{0.5} \times \frac{1}{(Response\ Time,\ ms)^{0.5}}\right]^2 \times 100 \tag{1}$$

$$Mental\ workload = \frac{(Relative\ Beta)_{Frontal}}{(Relative\ Theta)_{Frontal} + (Relative\ Alpha)_{Frontal}} \tag{2}$$

4 Results

4.1 Task Performance Result

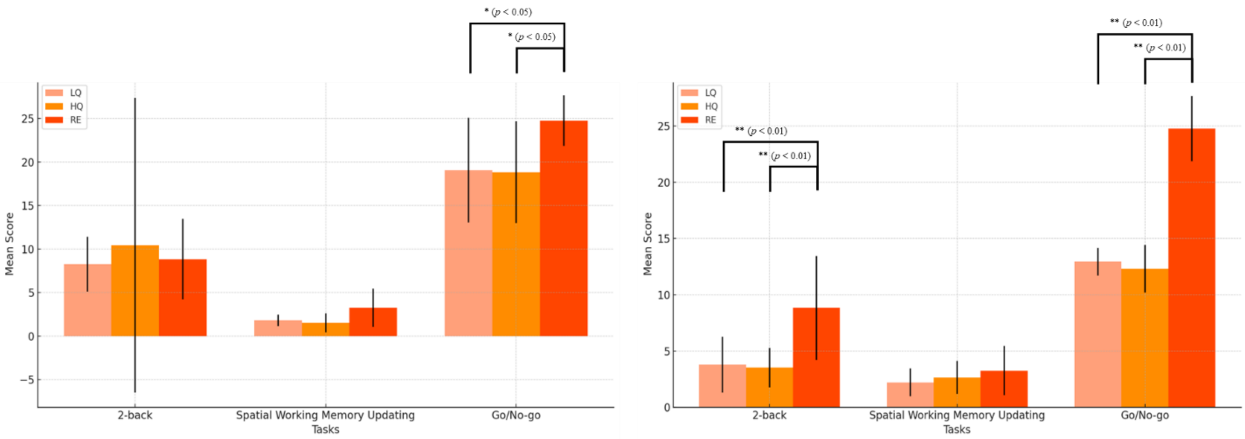
For the 2-back task, no significant differences in performance were observed among LQ, HQ, and RE in VR ($p = 0.350$). However, in MR, a significant difference was observed ($p < 0.001$), with RE outperforming HQ and LQ ($p < 0.01$). The performance advantage of MR may stem from the added realism of the real environment, which likely reduces the cognitive load.

In the Spatial Working Memory Updating Task (SWM), performance remained consistent across LQ, HQ, and RE in both VR ($p = 0.077$) and MR ($p = 0.356$). This indicates that visual fidelity does not have a strong impact on working memory tasks, regardless of the medium.

For the go/no-go task, RE significantly outperformed HQ and LQ across both VR ($p < 0.05$) and MR ($p < 0.001$). In both environments, RE outperformed HQ and LQ, with a post-hoc analysis showing that RE was significantly better than both HQ and LQ. This highlights the advantage of intuitive familiarity of the real environment in tasks requiring rapid decision-making and response inhibition.

Table 1. Statistical results of task performance across visual fidelity in VR and MR environments

Scenario	Task	Method	Type	Statistical Results					Post hoc
				Sum of squares	Df	Mean sqaure	F	p	
VR	2B	Kruskal Wallis	LQ HQ RE	2.101	2	-	-	0.350	-
	SWM	ANOVA-Welch	LQ HQ RE	20.7747	2	10.3874	4.8596	0.014* (0.077)	-
	GN	ANOVA	LQ HQ RE	271.1824	2	135.5912	5.1799	0.011^{*}	HQ=LQ<RE
MR	2B	ANOVA	LQ HQ RE	204.3144	2	102.1572	9.4686	0.000^{*}	HQ=LQ<RE
	SWM	ANOVA	LQ HQ RE	6.2397	2	3.1199	1.0706	0.356	-
	GN	ANOVA-Welch	LQ HQ RE	1121.5860	2	560.7930	113.9649	0.000^{*}	HQ=LQ<RE

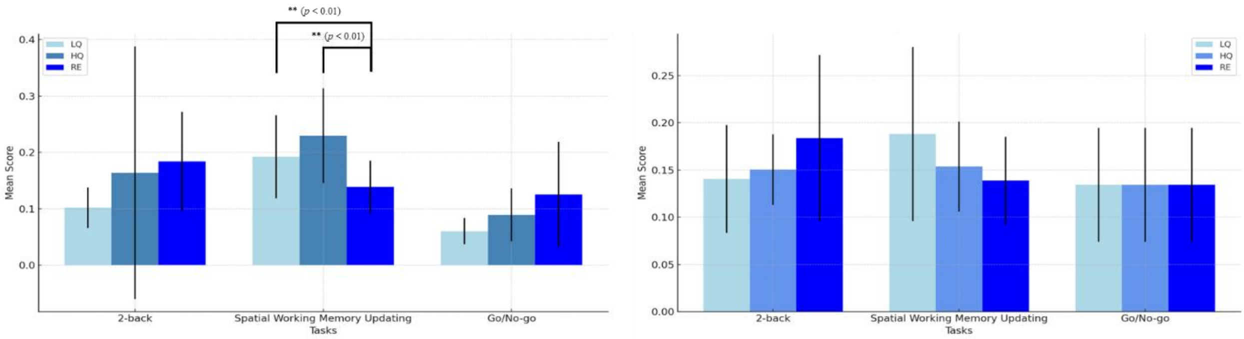


(a) VR Environment (b) MR Environment

Figure 3. Comparison of task performance across visual fidelity in VR and MR environments

Table 2. Statistical results of mental workload across visual fidelity in VR and MR environments

Scenario	Task	Method	Type	Statistical Results					Post hoc
				Sum of squares	Df	Mean sqaure	F	p	
VR	2B	Kruskal Wallis	LQ HQ RE	5.592	2	-	-	0.061	-
	SWM	ANOVA-Welch	LQ HQ RE	0.026	2	0.0128	3.3464	0.048* (0.036)	RE<LQ=HQ
	GN	ANOVA-Welch	LQ HQ RE	0.049	2	0.0247	3.1715	0.055 (0.027)	-
MR	2B	ANOVA-Welch	LQ HQ RE	0.012	2	0.006	1.3644	0.271	-
	SWM	ANOVA	LQ HQ RE	0.007	2	0.0033	0.6591	0.525	-
	GN	ANOVA	LQ HQ RE	0.002	2	0.0008	0.2246	0.800	-



(a) VR Environment

(b) MR Environment

Figure 4. Comparison of mental workload across visual fidelity in VR and MR environments

4.2 Mental Workload Result

In terms of mental workload, no significant differences were observed for the 2-back task across the environments in VR (p = 0.061) and MR (p = 0.271). This indicated that the cognitive load associated with the 2-back task was not significantly affected by the environment or visual fidelity levels.

For SWM, VR showed a significant difference in mental workload (p = 0.048), with post hoc analysis indicating a higher cognitive load in HQ than in RE. In contrast, no significant differences were observed in MR (p = 0.525), suggesting that visual fidelity did not affect the mental workload for this task in MR

The go/no-go task exhibited no significant differences in the mental workload across environments or media, as indicated by the results for both VR (p = 0.055) and MR (p = 0.800). This suggests that the visual fidelity levels did not significantly influence the cognitive load in this task.

5 Conclusion

This study examined the nuanced relationships among visual fidelity, task performance, and mental workload in VR and MR environments. For the 2-back task, the significant difference observed in MR but not in VR underscores the importance of considering specific medium when designing IVEs. In MR, the presence of real-world elements or cues may enhance task performance by providing familiar and intuitive spatial references that can reduce the cognitive demands. However, SWM showed consistent performance across all environments in both VR and MR, suggesting that visual fidelity had minimal effect on tasks involving working memory. By contrast, excessive visual detail in the HQ can burden cognitive resources without contributing to performance improvements. For the go/no-go task, the real environment consistently outperformed the VEs in both the VR and MR tasks, emphasizing the role of familiarity and intuitive interactions in optimizing task efficiency. The mental workload did not vary significantly for this task, indicating that the cognitive demands of response inhibition were stable regardless of environmental realism.

While this study was conducted in a L-shaped classroom setting, the cognitive process examined, such as executive function, memory, attention, are fundamental to human performance and can have implications beyond this specific environment. In real-world construction settings, particularly in open-plan sites and industrial environments, workers often navigate complex and unpredictable surroundings that require continuous cognitive adaptation. Given these considerations, our findings may provide valuable insights for applications in virtual construction environments, such as hazard perception training, safety simulation, and the understanding of complex procedural sequences. By integrating these cognitive insights into virtual construction platforms, training programs can replicate real-world conditions precisely, allowing for improved spatial awareness.

To enhance the generalizability of this study, future research should explore the way in which cognitive mechanisms influence decision-making and situational awareness in active construction environments. Expanding this research into dynamic, real-world settings could further validate its applicability in construction safety management.

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